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Refining PSO Applied to Electric Energy Cost Reduction in Water Pumping

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Abstract

The growing urban population growth necessitates that the water delivery sector uses safe, economical operations. In this context, an increasing number of operational routines has been tested that can adequately handle standard impositions and consumer's needs. The search for optimum routines for water pumping for startup and stopping and pump rotation variation has become increasingly common because of the need to reduce energy consumption, which therefore promotes the application of various optimization techniques. Among such techniques, special attention has been given to those inspired by nature, such as *Particle Swarm Optimization* (PSO), a technique based on the intelligence of groups, such as fish schools or insect swarms. This study presents a hybrid algorithm (simulator-optimizer) to determine optimized operational routines for pumping stations using PSO to define the number of pumps that are running (in nominal rotation) and rotations, which can therefore satisfy the operational restrictions at the time when the pumps are running. The performance evaluation is conducted by applying the model to an actual distribution network, where the energy cost was reduced by approximately 60%.

Keywords: Water supply system, energy efficiency, optimized operation, PSO

Introduction

One of the primary challenges that water supply companies currently face is the difficulty in dealing with urban growth, which is often disorganized, and maintaining safe, efficient water delivery. This growth incurs a constant need to expand the water delivery system, which increases energy consumption; this energy consumption is between two and three percent of the worldwide consumption (Vilanova and Balestieri, 2014)

Much of the delivery systems operational control is under the decision of operators who, by acting directly or by the command centre, load the operational rules based on their experience acquired from their career. However, the commands based on the operator's experience may lead to better performance when operations are executed without any knowledge of the system. Differently though, emergency situations, such as unpredicted stops of the pumping system or a duct rupture, may lead to emotionally affected decisions that are not always the most appropriate (Sandeep and Rakesh, 2011).

To reduce the reliance on empiricism in decision making, the literature proposes various tools that create responses from optimization mathematical models to aid operators in decision making. Among these models, hybrid models (optimizer-simulator) are capable of determining optimum manoeuvres for a given operational period. Optimized operational routines related to pump start-up and stopping manoeuvres or rotation changes by a frequency inverter significantly reduces energy consumption, which has been reported in literature. The most common optimization techniques used to search for better operational routines are dynamic programming (Jowitt and Germanopoulos, 1992) and evolutionary techniques, such as genetic algorithms: (Cunha, 2009), (Andrade, *et al.*, 2008), (Ribeiro, 2007), (Rodrigues, 2007), (Farmani *et al.*, 2007), evolutionary multi-objective techniques (Wang, Chang and Cheng, 2009), (Barán, Lücken and Sotelo, 2005) or even particle swarm optimization (PSO) (Al-Ani, 2012).

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The scan of the search area using meta-heuristics algorithms is arduous and imposes great computational efforts in problems with many variables. Hence, differently from the studies from literature, the present study develops an algorithm, hereby named Refining PSO, which consists of two steps. The objective of the algorithm is to reduce the computational effort for the simulation by decreasing the number of variables involved in the continuous stage (stage of rotation definition, phase two) once the operational status (shutdown or operating pump) is obtained in the first phase (discrete stage) by binary optimization. It is important to note that the strategy to define the pumps that are running versus the pumps that are not in operation avoids operational drawbacks because the search for only rotations may lead to low values, which in turn, can lead to undesirable physical phenomena, such as cavitation and vibration.

Materials and Methods

The pumping stations are responsible for much of the energy consumption and are the primary target in energy efficiency studies in the water supply sector. Studies suggest that on average, strategic operations with the objective of energy efficiency of hydraulic systems operations may lead to a 25% reduction in energy consumption. (Ramos, et al, 2012), (Moreira and Ramos, 2013).

Jowitt and Germanopoulos (1992) evaluated the electrical efficiency of motor-pump sets in a real network and considered the time variation of the demand. The authors used a simulation for an extensive period of time and used dynamic programming. The results were considered good, particularly the computational time spent in the study. Nevertheless, the treatments of the equations and restrictions of the hydraulic problem were arduous.

Cunha (2009) proposed real-time optimization of water delivery systems using binary optimization to represent the pump status problem. The GAlib generic algorithm was used as the optimization algorithm. According to Cunha (2009), although the search results for strategy routines (period of 24h) were good, the results were strongly influenced by penalties and operations of the optimization algorithm.

Ribeiro (2007) and Rodrigues (2007) modelled pumping systems using a frequency inverter and therefore searched for the best rotation for each hour of the day. Using a non-classical approach, the search for optimal rotations made it possible to work with continuous variables, which helped the search method. Both Ribeiro (2007) and Rodrigues (2007) used genetic algorithms as their optimization method. Ribeiro (2007) applied a fictitious network, whereas Rodrigues (2007) applied the model developed in a real network. Both authors obtained interesting values regarding the energy cost reduction. In the case of Ribeiro (2007), great improvement was also obtained by using variable-level reservoirs.

Finally, Al-Ani (2012) used MA-PSO (multi-agent PSO) with a bi-objective approach (pumping and maintenance costs minimization) to search for optimal routines for the motor-pump set. For the pump operation, this study modelled the stopping and start-up operations of pumps and thus only considered the working status of the machines. According to Al-Ani (2012), the algorithm proved to be efficient in reducing energy cost (approximately 9%) when applied to an actual network (Saskatoon West network).

By considering a previous study of the problem, the equations approached by this study are developed below, which presents the equations developed for continuous phase. Considering the change from nominal rotation (N_R) to an inferior rotation (N_i) by frequency modifications, the equation can be written in dimensionless form, and the nominal frequency (f) of 60 Hz can be expressed as

$$\boldsymbol{\alpha = \frac{Ni}{N_R} = \frac{fi}{60}} \qquad (1)$$

where f_i is the frequency that defines rotation (N_i), and α is the associated dimensionless rotation.

The change from nominal rotation to any rotation modifies the pump operating point, which can be expressed by its physical similarity laws:

$$\boldsymbol{Q = \alpha Q_R}, \quad \boldsymbol{H = \alpha^2 H_R}, \ \boldsymbol{P = \alpha^3 P_R} \qquad \boldsymbol{\eta_p = \eta_{pR}} \ (2)$$

where subscript p was used to specify the yield (η) associated with the pump, and subscript R is associated with the condition of nominal rotation. Q, H and P represent the flow rate, head and pump power, respectively.

The electric power $P(\alpha)$ required for pumping a flow rate Q for a specific head H for a given specific rotation α can be calculated as

$$\boldsymbol{P(\alpha) = \frac{\gamma Q H}{\eta_t}} \qquad (3)$$

where γ is the specific weight of water. The yield η_t represents the total yield of the set with the motor, inverter, pump, etc. Moreno (2007) suggests the following composition for this yield:

$$\boldsymbol{\eta_t = \eta_p . \eta_m . \eta_{sd} . \eta_c . \eta_l} \qquad (4)$$

where η_p, η_m, η_{sd}, η_c, and η_l are the yields of the pump, motor, inverter, and cables, respectively, which are associated with the loss of head in the pump set-up line.

The minimum desired consumption of electrical energy can be expressed for a period (Pe) of equal time intervals (i) by

$$\boldsymbol{Objective = min \sum_{i=1}^{n} \sum_{i=1}^{Pe} . c_i . P(\alpha)_{n,i} . i} \quad (5)$$

Subject to

$$p_{min} \leq p_{ref} \leq p_{max} \quad (6)$$

$$v_{min} \leq v_{ref} \leq v_{max} \quad (7)$$

$$N_{k,min} \leq N_k \leq N_{k,max} \quad (8)$$

$$n_{maneuver} \leq n_{max} \quad (9)$$

$$N_0 \leq N_{24} \quad (10)$$

where c_i is the electric energy cost for time interval *i*. The power $P(\alpha)_{n,i}$ is the electric power required for pumping to satisfy a demand *Q* by the system for a given period of time at a given head *H* of pump *n* to meet the operational requirements (Brentan, et al, 2013). Furthermore, p_{min} is the minimum dynamic pressure determined by the standard, p_{ref} is the pressure at a reference node at any time of the day, $p_{máx}$ is the maximum static pressure determined by the standard, v_{min} is the minimum velocity in any tube of the facility determined by the standard, v_{ref} is the velocity in a reference tube at any time of the day, $v_{máx}$ is the maximum velocity in any tube of the facility determined by the standard, $N_{k,mín}$ is the minimum operational level of reservoir *k* of the facility, N_k is the level of reservoir *k* at any time of the day, and $N_{k,máx}$ is the maximum operational level of reservoir *k*. Finally, $n_{manobra}$ is the number of stops and startup pump operations performed in the day, and $n_{máx}$ is the maximum number of manoeuvres allowed for the safety and maintenance of the equipment.

Optimization Using PSO

The bio-inspired algorithms are one of the techniques that have been gaining strength in the last few years. This large group of algorithms includes the PSO developed by Eberhart and Kennedy in 1995 and improved by Eberhart and Shi, who added the inertia constant (Eberhart and Kennedy, 1995) and (Eberhart and Shi, 2001). Since then, this algorithm has been widely used in continuous optimization problems of many variables or in problems using combination analysis and a discrete/continuous combination.

PSO is an algorithm based on a population, where particles are the elementary unit. The particles are composed of two vectors of size D (dimension of the problem), one that represents the particle position and the other that represents the displacement velocity. At each iteration n, the particle is updated by renewing the position information and velocity, which will subsequently be described (Eberhart and Kennedy, 1995).

The first step of the method is particle initiation for both the position and initial velocity, which is randomly performed within an interval of interest. The particles search for optimal points of the problem and update their velocities until one of the stop criteria for the problem is met, such as the maximum value with random error, maximum number of iterations, the absence of improvement in the object function for a given iteration interval; there are other stop criteria widely used in various numerical problems (Faires and Burden, 2002).

Considering that the problem contains i particles, the position of particle X_i in the swarm is described by a vector with D coordinates, where $X_i = (x_{i1}, x_{i2}, x_{i3}, \ldots x_{iD})$. This particle's velocity can also be described by a vector with D positions, where each vector component V_i represents the velocity of particle i in the D coordinate, i.e., $V_i = (v_{i1}, v_{i2}, v_{i3} \ldots v_{iD})$.

The particles compare their positions among themselves and "remember" their previous positions stored in their "memory". After evaluating the best solution, the method allows the particles far from the solution to move closer to the best solution. During the comparison, the best position of particle i is stored in a vector called *lbest* (*best local value*), described as $P_i = (p_{i1}, p_{i2}, p_{i3} \ldots p_{iD})$, and the best solution of the swarm is stored in a vector called *gbest* (*best global value*).

The swarm's behaviour can be described by the following equations:

$$v_{iD}^{n+1} = \left[w \cdot v_{iD}^{n} + \frac{c_1 \cdot r_1 \cdot (p_{iD}^{n} - x_{iD}^{n})}{\Delta t} + \frac{c_2 \cdot r_2 \cdot (g_{iD}^{n} - x_{iD}^{n})}{\Delta t} \right] \quad (11)$$

$$\boldsymbol{x_{iD}^{n+1} = x_{iD}^{n} + v_{iD}^{n+1} . \Delta t} \quad (12)$$

where d = 1,2,…D, n = 1,2,… N, and N is the number of iterations. Additionally, r_1 and r_2 are randomly chosen numbers within the interval [0,1], and n represents the current iteration.

From equation (11), it can be observed that for each iteration the particle position is updated. Part of this update is marked by a coefficient that has information on the best positions experienced by the particle, which is called the *cognitive coefficient* (c_1). Another aspect of the update is influenced by the information on the best positions experienced by the group, and such information is computed at a velocity by a coefficient called the *social coefficient* (c_2). Finally, the velocity is also updated by a coefficient named *weight* or the *inertia coefficient* (*w*). (Eberhart and Kennedy, 1995)

In the continuous problem, the particle "flies over" the entire search space. In the case of a binary discrete space, the particle scans the vertices of a D-dimensional hypercube and searches for the best solution vertex. In comparison to the algorithms for continuous spaces, where the flying-over velocity is easily interpreted as the particle displacement rate from a position x_{id} to a position $x_{i+1,d}$, which can be easily determined by equation (7), the interpretation of velocity in the binary case is more complex. For this case, the velocity is probabilistic and can be understood as the chance of position x_{id} being 1. (Eberhart and Kennedy, 1997)

To transform the velocity into a position, a sigmoidal function is typically used, according to the following relation:

$$\text{If rand()} < S(v_{id}), \text{ then } x_{id} = 1; \qquad (13)$$

where *rand()* is a function that generates a random number in the interval [0,1], and $S(v_{id})$ is the sigmoidal function applied to the velocity; the transformation between the value of rand() in the interval [0,1] can thus be controlled. Therefore, depending on velocity, the probability is responsible for updating the particle's position (Eberhart and Kennedy, 1997)

PSO and most of the bio-inspired methods are unrestricted search methods, and hence, these methods do not have treatment mechanisms for the restrictions inside their search routines. Therefore, a way to transform a restricted problem into an unrestricted problem for the applicability of one of the unrestricted algorithms is required (Pillo and Grippo, 1989). One common, widely used form in restricted engineering problems is using a penalty function, which adds a certain value from the object function, whose role is to treat deviations of variables or associated parameters relative to the pre-defined restrictions (Yeniay, 2005).

As the restricted problem treatment in this study, a penalty method for pressures named “Fictitious Machine Method” was used with the following formulation: let p_{ref} be the necessary pressure in a reference node, in water column meters, and Q_{tub} be the flow rate in the pipes, in m³/s, which arrives at this node. It is possible to calculate the power of a fictitious hydraulic machine, which regularizes the pressure at this node, and works as a pump when the pressure at the reference node is lower than the desired pressure or works as a turbine when the pressure at the reference node is higher than the desired pressure. By multiplying the required power by each time interval and by the energy cost at this time interval, the cost of establishing the necessary pressure in the observed node is obtained. The power of the fictitious hydraulic machine can be calculated with the following equation:

$$P_{mf} = \frac{\gamma Q_{tub}\,|P - P_{REF}|}{\eta} \qquad (14)$$

where γ is the specific weight of the fluid transported by the studied system, and P is the pressure at the node.

Hence, the cost associated with the fictitious machine and the consequent penalty of the method can be written as

$$\boldsymbol{Pen = k.P_{mf}.c.f} \qquad (15)$$

where c is the energy cost, f is the surcharge factor, and k is a factor related to the convergence characteristics of the method, which is used as a scale factor.

For the penalties of the velocities and stopping/start-up pump operations, the classical development of penalty functions was used, which was presented by Parsopoulos and Vrahatis (2002) and can be written as

$$\boldsymbol{\rho(x) = \lambda.(|x - x'|)^t} \qquad (16)$$

where λ is a scale multiplying factor, |x-x’| is the modulus of the total deviation between the limit value x’ and the variable x, and t is an exponent that defines the behaviour of the penalty function.

Results and Discussion

As a case study, the system designed by Carrijo (2004) is used to determine the optimal pump manoeuvres using a genetic algorithm. This system is located in the city of Goiânia, Brazil and is part of the delivery network for a population of approximately 1.2 million people. The demand nodes represent derivations to sectors of representative networks, and thus, the flow rates attributed to such nodes are the demands of the sectors delivered by each derivation (Carrijo, 2004). The figure below illustrates the topology of this network, and the tables display the physical and hydraulic characteristics of the network:

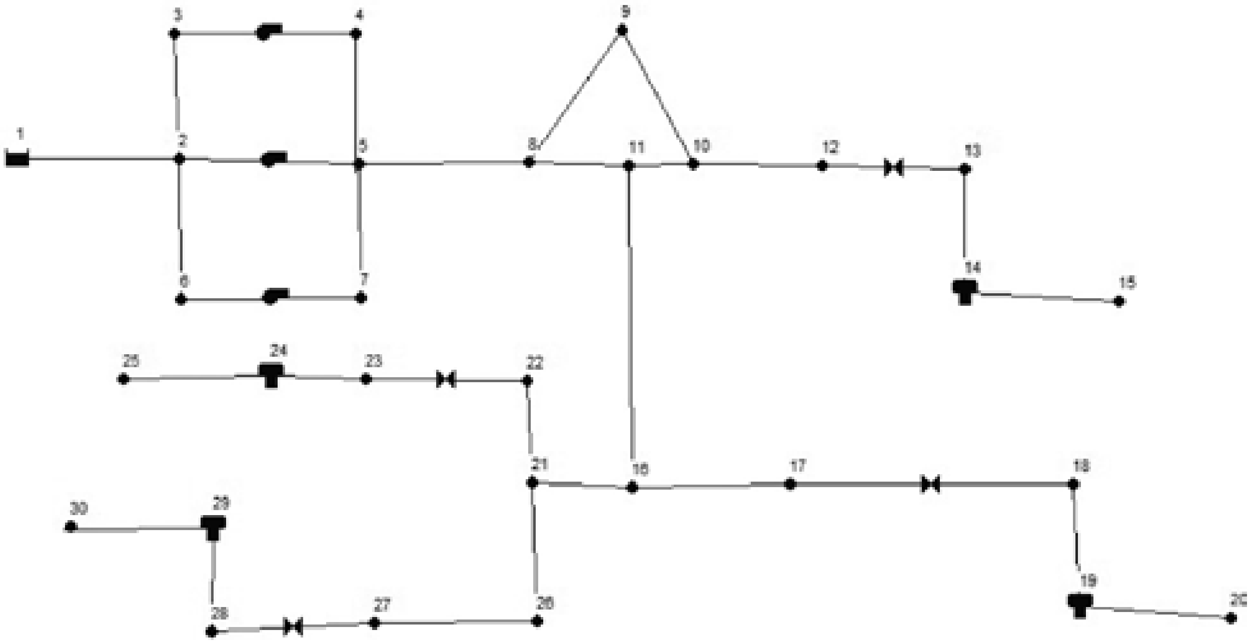

Figure 1: Actual topology studied by Carrijo (2004)

Table 1: Variable level reservoirs (VLR) data, CARRIJO (2004)

VLR	Volume (m³)	Max Level (m)	Level (m)
14	10000	6.0	858.0
19	5000	5.5	561.5
24	10000	7.0	836.5
29	3000	5.0	863.0

Table 2: Flow rate control valve data, CARRIJO (2004)

Valve	Diameter (mm)	Flow Rate (l/s)
29	600	616
30	600	496
31	800	542
32	500	474

Table 3: Consumption nodes demand and level, CARRIJO (2004)

Demand Nodes	Level (m)	Max Demand (l/s)
15	843.50	616
20	846.70	496
25	820.65	474
30	846.80	542

Table 4: Nodes level, CARRIJO (2004)

Node	Level (m)
02	788.10
03	788.15
04	788.12
05	788.10
06	788.12
07	788.13
08	801.20
09	823.10
10	845.15
11	840.05
12	845.12
13	845.12
16	848.20
17	850.15
18	850.15
21	852.20
22	832.30
23	832.25
26	850.10
27	850.15
28	850.13

Table 5: Pipe data, CARRIJO (2004)

Pipe	Level (m)	Diameter (mm)
01	50	1500
02	5	1200
03	5	1200
04	5	1200
05	5	1200
06	2050	1500
07	2840	600
08	3990	800
09	200	800
10	4725	1372
11	120	800
12	50	800
13	10	800
14	1050	1372
15	5368	1200
16	441	800
17	50	800
18	10	800
19	2070	800
20	50	1000
21	50	100
22	10	100
23	473	800
24	50	800
25	10	800

Table 6: Neutral Demand Curve, CARRIJO (2004)

Hour	Multiplying Factor
01	0.30
02	0.15
03	0.20
04	0.45
05	0.43
06	0.55
07	0.60
08	0.80
09	0.90
10	1.00
11	0.90
12	0.80
13	0.70
14	0.65
15	0.65
16	0.60
17	0.60
18	0.63
19	0.68
20	0.65
21	0.60
22	0.30
23	0.30
24	0.30

The study considered a minimum water level in the reservoirs of 1.5 m, and the pumps curves were defined with one point, i.e., using a hydraulic head of 85 m and a flow rate of 895 l/s. The value of the coefficient C of the Hazen-Williams equation that was adopted was 100 for all of the pipes, which is in accordance with the study by Carrijo (2004). Furthermore, for the operational cost studies, an 80% efficiency was used for the motor-pump sets. The study by Carrijo (2004) considered the energy cost as Brazilian Real (R$) 0.17076/kWh during the peak hour and R$0.0816/kWh at all other times. In turn, the demand at the peak hour is considered to be 26.38 R$/kW and at all other times is considered to be R$8.66/kW. With all of the simulations performed for the previously detailed network, the following result is obtained for the cost of the operational routine:

Table 7: Operational cost, comparative table

Type of simulated scenario	Operational Cost
PSO-R	2213.80
AG	2494.33

It can be observed that the routine found with PSO-R works with higher rotations that reduce the occurrence of excessive vibration problems, and therefore, cavitation problems can be avoided. Next, comparative graphs are presented with the reservoir level and pressure at the control nodes. By observing the reservoir level fluctuation graphs, the significant level variation of reservoir 29 is observed once again, which reflects the pressure variation at node 30. Moreover, the level of fluctuation caused by the routine found with PSO-R leads to emptying in moments of greatest water consumption and higher energy cost.

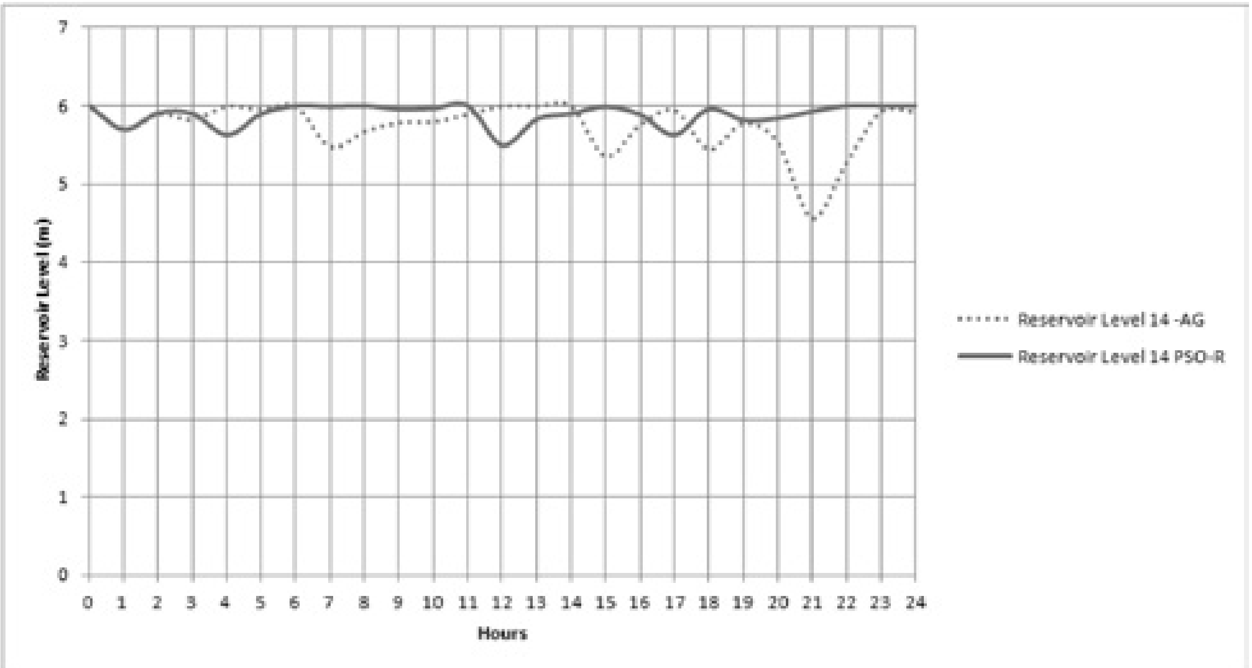

Figure 2: Level fluctuation of reservoir 14: comparison of techniques

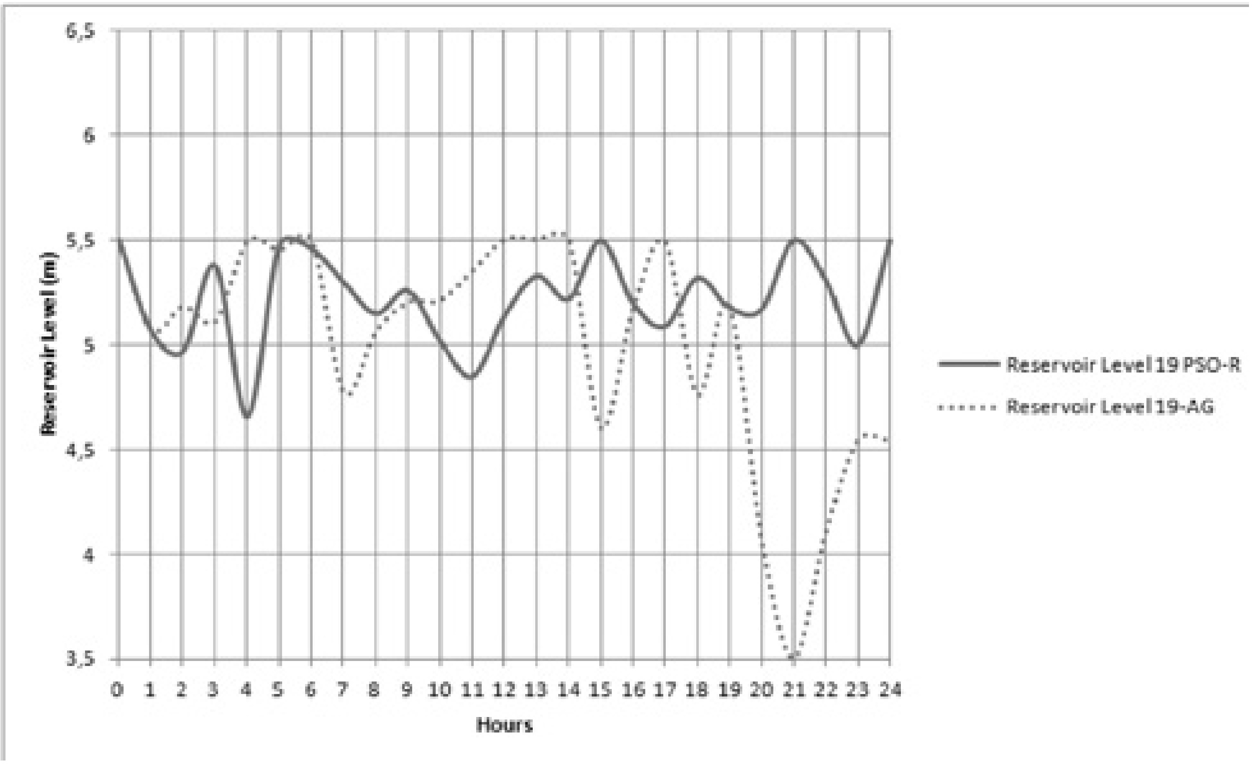

Figure 3: Level fluctuation of reservoir 19: comparison of techniques

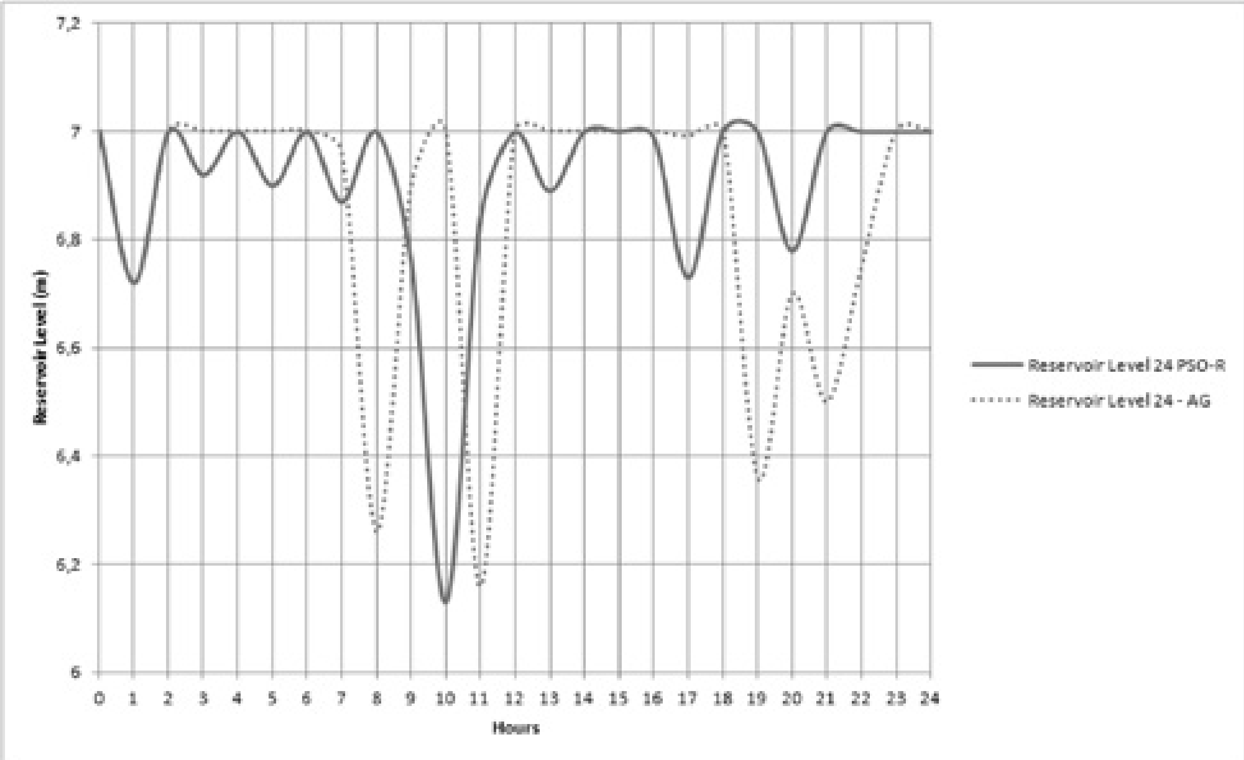

Figure 4: Level fluctuation of reservoir 24: comparison of techniques

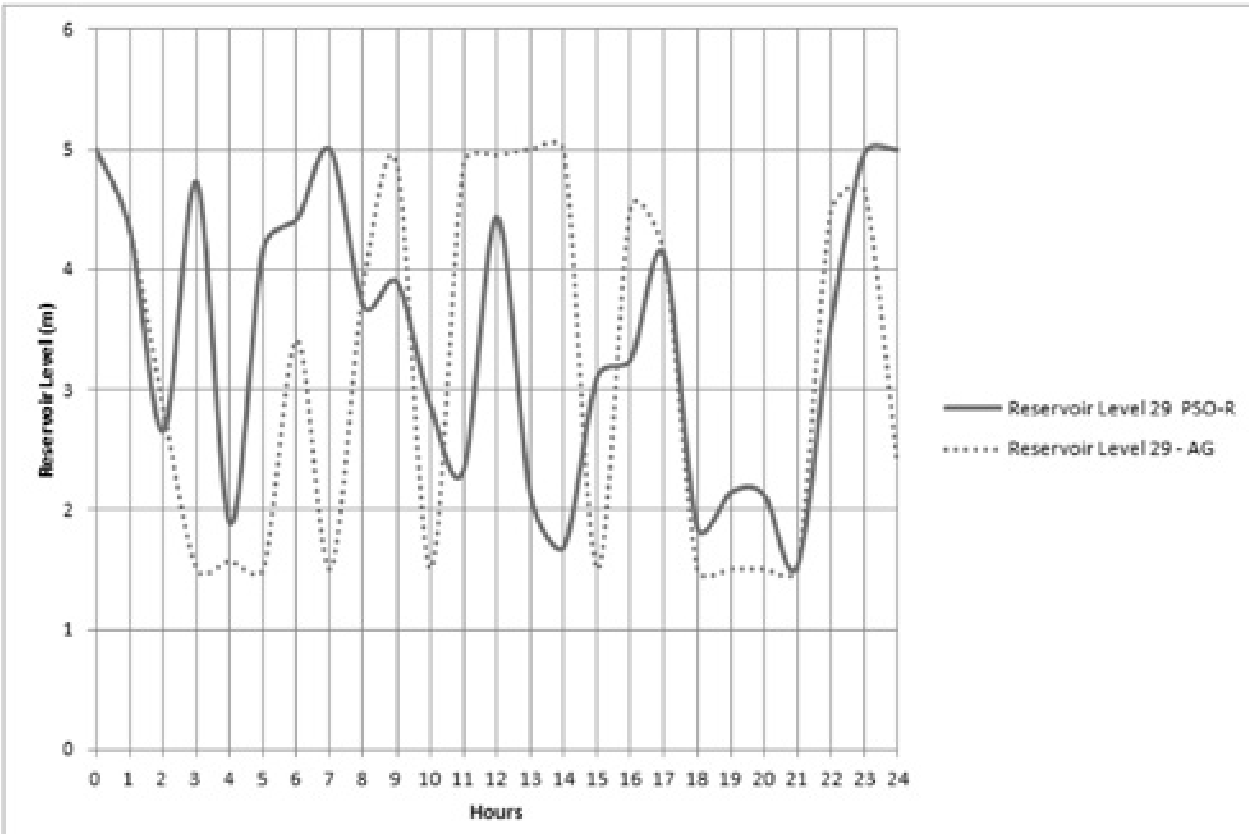

Figure 5: Level fluctuation of reservoir 29: comparison of techniques

Next, the comparative graphs of the pressure evolution in the reference nodes are displayed.

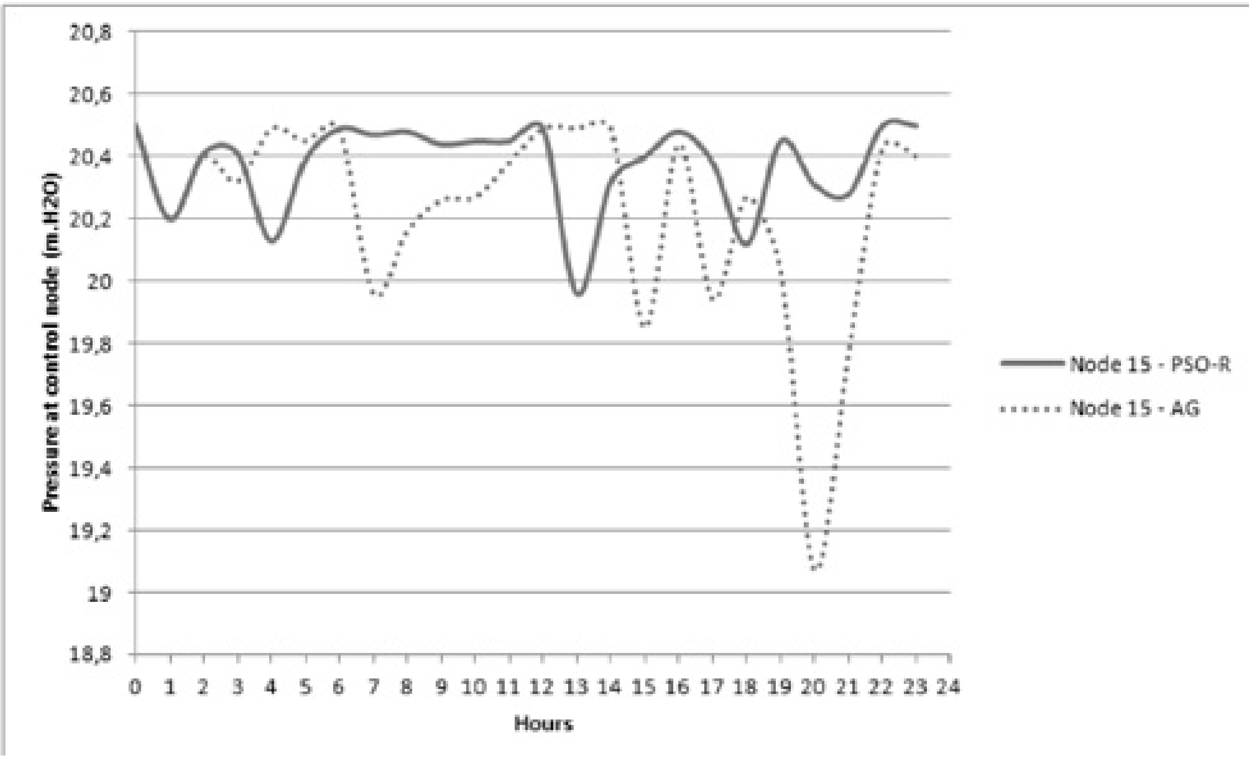

Figure 6: Pressure variation at node 15: comparison of techniques

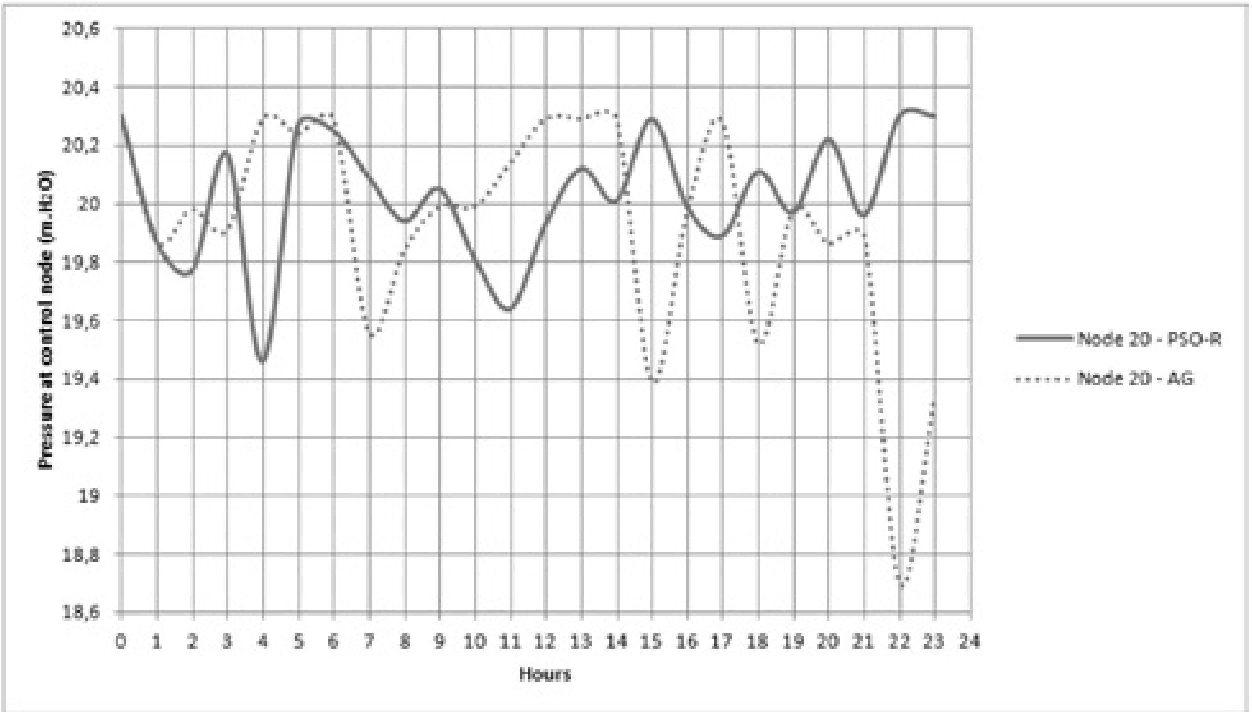

Figure 7: Pressure variation at node 20: comparison of techniques

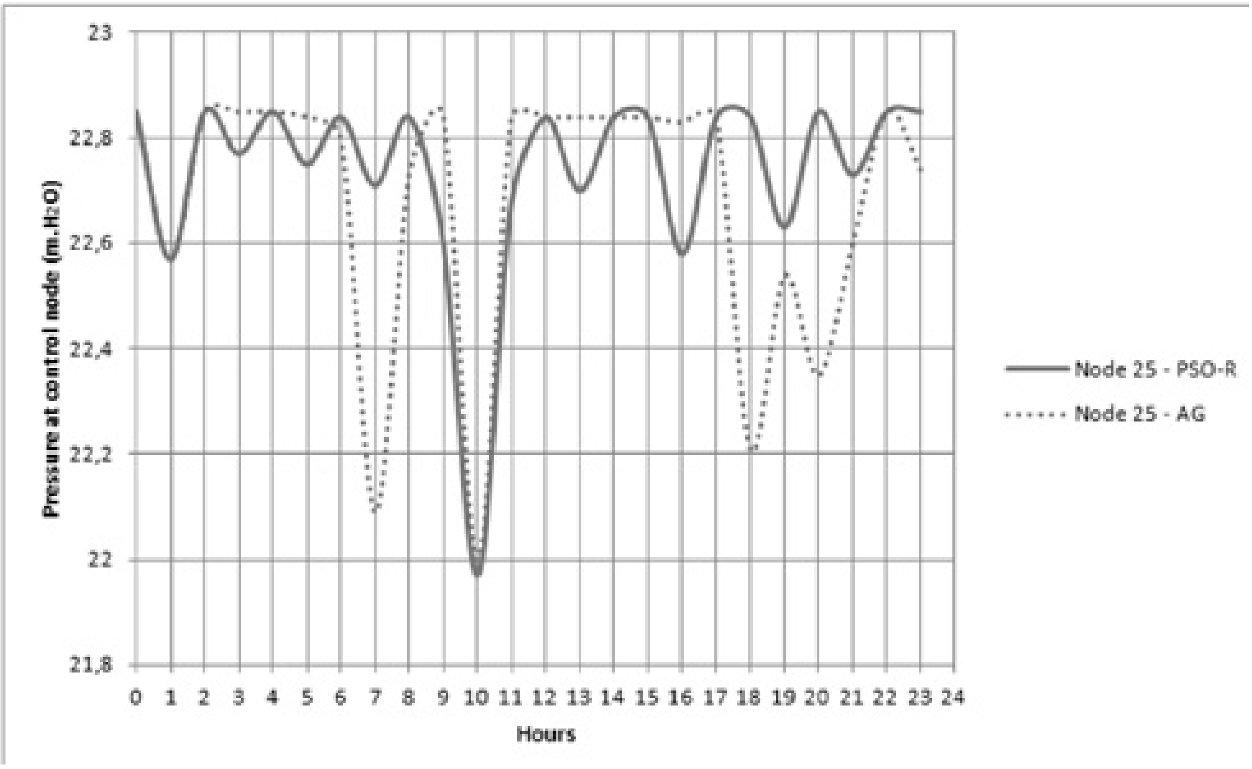

Figure 8: Pressure variation at node 25: comparison of techniques

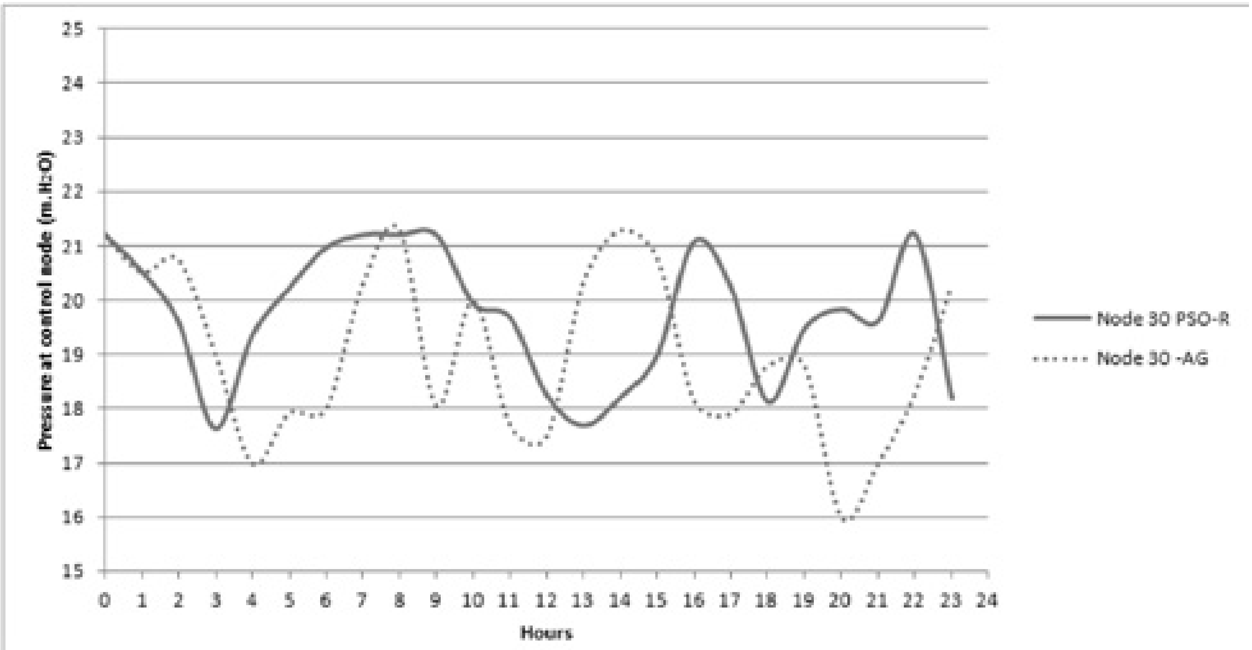

Figure 9: Pressure variation at node 30: comparison of techniques

Conclusions

By analysing the network from Carrijo (2004) using the PSO-R, the performance of the optimizer was obtained in terms of the final operation cost compared with that of the genetic algorithm. In economic terms, when compared with the fixed rotation scenario, the PSO-R results in a reduction of 63.5% in operational cost.

The PSO-R performed 888000 evaluations of the objective function (216 particles with 3000 iterations in the binary phase, and 120 particles and 2000 iterations in the continuous phase) for the presented network, where the stop criterion for both phases was the absence of improvement of the objective function for at least 100 consecutive iterations.

From an operational point of view, the method proved to be effective in determining the operational rules for the assessed network, which resulted in high energy savings by reducing the operational cost of the pumping systems. Furthermore, the optimized routine resulted in better use of the variable level reservoir, whose emptying and filling movement assured a better water quality.

Moreover, the optimized routine exhibited less variable behaviour for the evaluated pressures at the relevant nodes of the studied system. The less abrupt pressure variation softens the stresses on the pipes, which subsequently increases the useful life of the pipes due to less fatigue processes.

By assessing the optimization method in a continuous phase, the results indicated that the lower limit for the specific rotations requires further evaluation because in several cases, the frequent use of a specific low rotation may lead to an undesirable phenomenon, such as cavitation, excessive vibration, or even overheating the equipment.

Finally, the use of computational tools to operate delivery systems can be extremely useful when used with clear knowledge of hydraulic issues and computational methods involved in the problem. The indiscriminate use of computational models could create serious issues for system operations, and therefore, there is a need to provide tools to the operators that can unite the operation practice with the ease of the computational tools.

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